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Risk based maintenance of offshore wind turbines using Bayesian networks

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ABSTRACT

This paper presents how Bayesian networks can be used to make optimal decisions for repairs of offshore wind turbines. The Bayesian network is an efficient tool for updating a deterioration model whenever new information becomes available from inspections/monitoring. The optimal decision is found such that the preventive maintenance effort is balanced against the costs to corrective maintenance including indirect costs to reduced production. The basis for the optimization is the risk based Bayesian decision theory. The method is demonstrated through an application example.

KEYWORDS

Wind turbines, Maintenance, Bayesian networks, Risk based optimization

1 INTRODUCTION

Operation and maintenance is an important issue for offshore wind turbines, as the costs are large, up to 25-30% of the cost of energy. Especially a large number of component failures lead to reduced power production and a need for corrective maintenance. These costs can be reduced by applying preventive maintenance strategies, such as condition based maintenance. Here decisions on repairs are made based on information gained using condition monitoring. Condition monitoring methods are subject to uncertainties, and more optimal decisions can be made if the monitoring results are combined with all available knowledge from past experience and theoretical models using Bayesian updating. Risk based methods can then be applied to find the optimal maintenance strategy, and make optimal decisions on preventive repairs, see the framework in [1]. Bayesian networks and influence diagrams can be used for updating a damage model, whenever new information becomes available, and to find the optimal decisions.

2 BAYESIAN NETWORKS

A Bayesian network is a graphical model that consists of nodes, representing stochastic variables, and links, representing conditional dependencies among them. A link from A to B

means that B is caused by A, and A is called the parent of B, and B the child of A. For each node in the Bayesian network the conditional probability distribution should be specified conditional of the parents, thus for nodes without parents the marginal distribution should be specified. The network can then be used to find the posterior distributions using Bayesian updating based on Bayes formula. See [2] for an introduction to Bayesian networks, and [3] for a framework for deterioration modelling using Bayesian networks.

2.1 Deterioration modelling

In the present application it is assumed that the overall health of a component can be described by a damage model. Inspections are performed on a regular interval, and there it is possible to measure the health of the component, but with some uncertainty. The Bayesian network for this model consists of a number of equal time slices, one for each time step, and a first time slice with the initial values. The first part of the Bayesian network with two time slices is shown in Figure 1. The health of the component is represented by the damage size, D, that increases with time. In the damage model two parameters are modelled by random variables, μ and A, which are time invariant and variant parameters respectively. The inspection result is included in the node Ins.

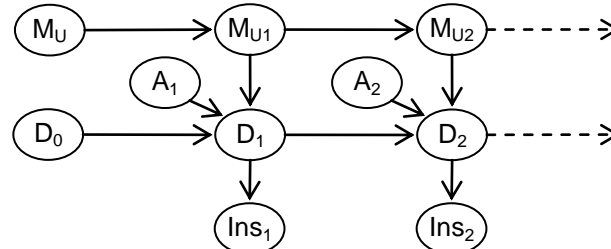


Figure 1: Bayesian network for updating of the damage size. D: damage size, Ins: inspection, A, μ : damage parameters.

2.2 Influence diagram

The network presented above can be used for updating the probability distribution of the damage size, and if a failure criterion is formulated, the probability of failure can be found. The Bayesian network can be extended to an influence diagram, which can be used for finding optimal decisions. An influence diagram consists of nodes and links, like the Bayesian network, but there are two additional types of nodes, utility nodes and decision nodes, shown with diamonds and rectangles respectively. The utility nodes are used to include the costs in the model, in this case the cost of failure (including lost production and cost of corrective repair), and the cost of preventive repairs. Decision nodes are used to include decisions in the model, here the decision of making a preventive repair.

The optimal decisions for the repair times are the ones that give the smallest expected costs through the lifetime. These can be found using a Bayesian pre-posterior decision analysis, where decision policies are included for all future decisions, see theory in [4]. In this paper a LIMID (Limited Memory Influence Diagram) has been used for the optimization, see [5].

3 APPLICATION EXAMPLE

It is assumed that an inspection is performed every year, and after each inspection it can be decided to make a preventive repair. The component has a mean time between failures of 8 years, and the damage development is described by Paris law. The wind turbine is assumed to have a lifetime of 20 years, and the first part of the LIMID is shown in Figure 2.

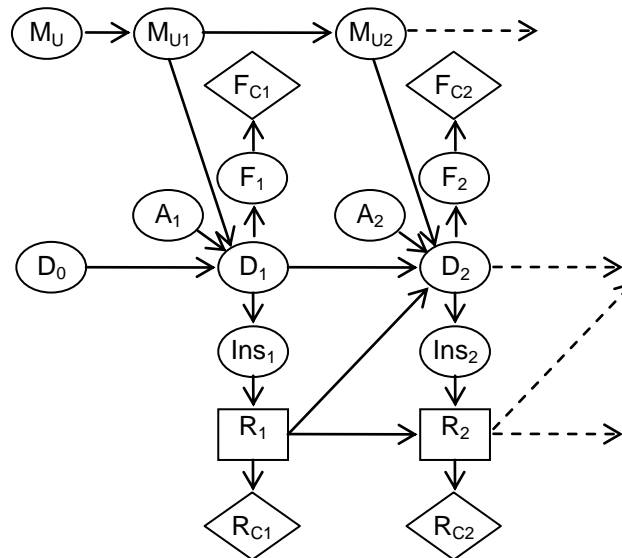


Figure 2: Influence diagram for finding optimal repair decisions. D: damage size, F: failure, R: repair, Ins: inspection, A, M_U : damage parameters,

Failure occurs at the damage size 1, and at the inspections there is assumed to be an additive measurement error that is normal distributed with mean zero and standard deviation 0.05. In general the variables used in the model are continuous, but for a LIMID it is necessary to discretize all variables. The variable representing the damage size, D , is discretized in 30 states, where the last state is failure. The other states have exponentially increasing size, and are numbered 1 to 29. For details about the damage model and discretisation of variables, see [6]. The observations used for the case study is shown in Table 1.

Table 1: Observations for the case study. Numbers refer to states.

Year	1	2	3	4	5	6	7	8	9	10
Observation	14	15	21	17	19	23	27	28	29	Failure

3.1 Results

The probability of failure calculated based on the information available on the last time step, and the expected utility for the decisions repair and no repair is shown in Figure 3. In year 7 the utility of repairing is larger than the utility of not repairing, and thus a repair should be performed.

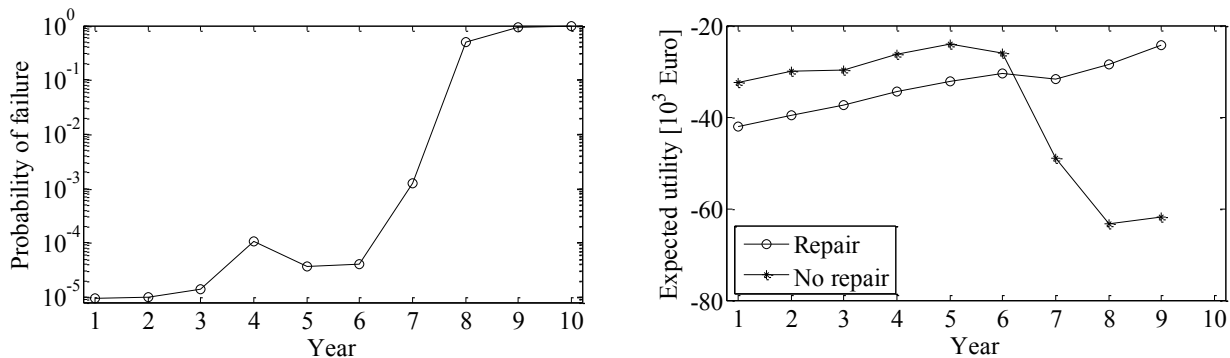


Figure 3: Probability of failure and expected utility for case study.

4 CONCLUSIONS

This paper demonstrates how Bayesian graphical models can be used to assist in optimal decision making for preventive repairs of offshore wind turbines. The method can be applied to components where a damage model can be formulated.

5 ACKNOWLEDGEMENTS

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